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National resilience assessment and improvement based on multi-source data: Evidence from countries along the belt and road

Jianping Li [a], Jiaxin Yuan [a], Weilan Suo [b,*]

[a] *School of Economics and Management, University of Chinese Academy of Sciences, Beijing, 100190, China*
[b] *Institutes of Science and Development, Chinese Academy of Sciences, Beijing, 100190, China*

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ABSTRACT

National resilience is a consensus benchmark to characterize the ability of disaster resistance of a country. The occurrence of various disasters and the ravages of COVID-19 have created urgent needs in assessing and improving the national resilience of countries, especially for countries along the Belt and Road (i.e., B&R countries) with multiple disasters with high frequency and great losses. To accurately depict the national resilience profile, a three-dimensional assessment model based on multi-source data is proposed, where the diversity of losses, fusion utilization of disaster and macro-indicator data, and several refined elements are involved. Using the proposed assessment model, the national resilience of 64 B&R countries is clarified based on more than 13,000 records involving 17 types of disasters and 5 macro-indicators. However, their assessment results are not optimistic, the dimensional resilience are generally trend-synchronized and individual difference in a single dimension, and approximately one-half of countries do not obtain resilience growth over time. To further explore the applicable solutions for national resilience improvement, a coefficient-adjusted stepwise regression model with 20 macro-indicator regressors is developed based on more than 19,000 records. This study provides the quantified model support and a solution reference for national resilience assessment and improvement, which contributes to addressing the global national resilience deficit and promoting the high-quality development of B&R construction.

1. Introduction

Despite active efforts at disaster prevention and mitigation, the losses caused by disasters have increased [1,2]. Specifically, the occurrence of disasters from 2000 to 2019 resulted in economic losses of nearly 3 trillion dollars, affecting more than 4 billion people and, more seriously, killing approximately 1.23 million people [3]. In recent years, the ravages of COVID-19 have paralyzed health systems resilience in almost every country [4]. Facing the devastating impact, recovering quickly from these disasters has been a concern of scholars and government administrators [5,6]. National resilience, defined as the ability of a country to return to its original state quickly and maintain its structure and function after unanticipated disasters, has become a benchmark to characterize the disaster resistance of a country [7]. The situation of countries along the “Silk Road Economic Belt and the 21st-Century Maritime Silk Road” (abbreviated as the Belt and Road) [8], i.e., B&R countries, located in the Asian, European, and African continents and their adjacent seas [8,9], was more severe because of multiple disasters with high frequency and great losses [3,10]. Emergency Events Database (EM-DAT) data from 1989 to 2021 indicate that 8 of the 10 worst-hit countries (ranked by the number of deaths) belong to the B&R

* Corresponding author.
E-mail address: suoweilan@casisd.cn (W. Suo).

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countries. Therefore, it is urgent to conduct a national resilience assessment and improvement for these B&R countries, which is beneficial to compensate for the shortcomings in national resilience worldwide and improve global resilience. In addition, the B&R Initiative advocates global balanced and sustainable development [11,12], and the study of the national resilience of B&R countries is conducive to the high-quality development of the B&R construction.

The original concept of resilience put forward by Holling [13] was applied to ecosystem study and subsequently extended to the social science studies [4,6,14]. Although social science scholars have conducted many studies on national resilience, there is no consensus on how to measure national resilience [15], and existing assessment models still have limitations in the dimensional characterization and quantification of national resilience as well as the utilization of data [16–18]. To accurately depict the national resilience profile, we propose a three-dimensional assessment model based on multi-source data with the considerations of the diversity of losses, fusion utilization of disaster and macro-indicator data, and several refined elements. Subsequently, to demonstrate the applicability of the proposed assessment model, the national resilience of 64 B&R countries is clarified using multi-source data which includes more than 13,000 records involving 17 types of disasters and 5 macro-indicators. The obtained assessment results are analyzed from the perspectives of overview, individual dimension, and resilience change. To further explore the applicable solutions for national resilience improvement, a coefficient-adjusted stepwise regression model with 20 macro-indicator regressors is developed based on more than 19,000 records. Furthermore, a comparison of studies on national resilience assessment and several valuable findings regarding identified critical factors for national resilience improvement are discussed.

The rest of this study is organized as follows. In Section 2, a literature survey is conducted to review existing studies on national resilience assessment. In Section 3, a methodology for national resilience assessment is elaborated. In Section 4, the assessment results are analyzed to clarify the national resilience profile of 64 B&R countries. In Section 5, the resilience improvement solutions for these B&R countries are explored. In Section 6, a comparison of studies on national resilience assessment and discussion for national resilience improvement are conducted. Finally, in Section 7, the main research work and research findings, as well as the contributions, limitations, and future work are summarized.

2. Literature survey

In existing studies, it has been shown that a country may face various disasters, such as hurricanes, rainstorms, and earthquakes, which will seriously destroy the normal operation of social and economic systems and other aspects [19,20]. Hence, some scholars assessed national resilience by establishing a macro-indicator system [16,21–23]. For example, Sajjad [22] assessed the national resilience of Pakistan using economic, institutional, and social macro-indicators. However, there has been much debate on these studies. One issue concerns macro-indicators. The direct and instantaneous influence of disaster usually cannot be reflected by macro-indicators, which may lead to biased and severely lagged resilience results. The other issue is subjectively assigning weight to macro-indicators. Assigning appropriate weights to each macro-indicator is a critical but laborious task, especially for national resilience assessment with many macro-indicators; on the other hand, subjectively assigning weights would make similar indicator systems likely to yield dramatically different resilience results even when the same data are used [17].

In order to solve the aforementioned problems, several resilience functions were constructed based on disaster data, which can directly reflect the disaster impact and without artificial weighting. Some scholars constructed the integral functions based on the data from a single type of disaster to measure the system recovery level in time dimension [24–26]. For example, Bruneau et al. [24] constructed an integral function to assess seismic resilience from the perspectives of system robustness and recovery rapidity. Other scholars constructed the ratio functions based on multi-disaster data. For example, Zhang and Huang [27] constructed a ratio function of the estimated disaster losses to the actual disaster losses to assess the national resilience of 207 countries using multi-disaster data from 1966 to 2015. In fact, based on the work of Yonson and Noy [26], it can be verified that when only a single type of disaster is involved, the ratio function of estimated losses to actual losses is essentially consistent with the integral function using the loss curve reflecting the time dimension.

Existing studies have provided a valuable reference for national resilience assessment, but there are still some issues that need to be improved: 1) One-sided consideration of resilience dimension. Usually, disasters would cause human and economic losses, while in existing studies, only single type of loss was considered [26–28]. A partial consideration of human or economic losses is not conducive to recognizing resilience dimension from a comprehensive perspective. 2) Insufficient utilization of data resources. Strong availability and coverage are the merits of macro-indicator data, while disaster data can reflect the impact of disasters timely. Existing studies used either macro-indicator or disaster data to assess national resilience [26,27,29], and how to comprehensively utilize them deserves further study. 3) Rough consideration of quantification elements for resilience assessment. Differences in magnitude of a given types of disasters were ignored when using disaster data [27,30,31]. Meanwhile, the effect of inflation was not considered in calculating economic losses [26,32]. 4) Unconvincing solutions for resilience improvement. Simple linear regression or even textual qualitative descriptions were used to identify critical factors for resilience improvement [22,27,33], which may lead to biased conclusions.

The above issues are not conducive to ensuring the accuracy of national resilience assessment and the applicability of resilience improvement solutions. Therefore, it is necessary to propose more scientific and reasonable national resilience assessment and improvement models from the following aspects.

- *The consideration of diversity of losses.* Multiple aspects of losses caused by disasters should be considered, e.g., the number of deaths, the number of people affected, and the economic loss, to construct a multi-dimensional national resilience assessment model. This is beneficial to make the dimensional characterization of national resilience more scientific.

- *The fusion utilization of multi-source data.* The utilization value of either macro-indicator or disaster data to national resilience assessment has been verified in existing studies. The fusion utilization of macro-indicator and disaster data helps to complement and adjust each other, resulting in a more accurate, complete, and reliable assessment of national resilience than a single information source.
- *A necessary consideration of several refined elements*. The effect of disaster magnitude can be integrated into the national resilience assessments to reflect the true danger level of disasters, the inflation rate can be utilized to discount the value of economic losses in different years, and the differences in the geographic landscapes of different countries can be quantified by introducing physiological density. This is beneficial to make the process and results of national resilience assessment more reasonable.
- *A reliable solution for national resilience improvement*. A coefficient-adjusted stepwise regression model with multiple macro-indicator regressors can be developed to identify critical factors for national resilience improvement, where the coefficients of insignificant regressors are solved by the constructed function based on correlation coefficient matrix. The developed model can avoid the effects of multicollinearity and spurious regression, which is beneficial to provide a feasible and efficient solution reference for national resilience improvement.

3. Methodology for national resilience assessment

In this section, the proposed three-dimensional assessment model is elaborated to conduct the national resilience assessment of 64 B&R countries. Firstly, the conceptual framework and data and notations are presented. Subsequently, dimensional resilience calculation and aggregation are described, respectively.

3.1. Framework

To support national resilience assessment, a conceptual framework is presented (see Fig. 1), which includes two parts, i.e., collection and pre-processing of multi-source data, as well as dimensional resilience calculation and aggregation. A brief description of each part is presented below.

3.2. Data and notations

3.2.1. Data

Based on the list of the first batch of countries to sign the B&R Initiative, 64 B&R countries are considered in this paper. They are presented in the form of three-letter abbreviation country codes from International Olympic Committee, i.e., IND, CHN, IRN, PAK, PHL, IDN, TUR, BGD, POL, VNM, AFG, EGY, IRQ, NPL, LBN, LKA, MNG, ALB, THA, JOR, MMR, SAU, BGR, MYS, SYR, LAO, ARE, HUN, ISR, ROU, KHM, OMN, BHR, MDV, BTN, SGP, GEO, TJK, RUS, UKR, YEM, ARM, AZE, KGZ, HRV, LTU, UZB, BLR, MKD, KAZ, TKM, MDA, EST, CZE, SVK, SVN, BIH, KWT, BRN, LVA, TLS, MNE, SRB, and QAT.

Disaster data and macro-indicator data are both utilized in the national resilience assessment of these B&R countries. Based on the analysis of existing studies and actual requirements, as well as the consideration of data availability, 17 types of disasters are determined, involving storm, flood, drought, landslide, transport accident, miscellaneous accident, industrial accident, earthquake, glacial lake outburst, volcanic activity, wildfire, insect infestation, extreme temperature, epidemic (including COVID-19), mass movement (dry), extra-terrestrial impact, and complex disasters. The common disaster data (excluding COVID-19) related to these B&R countries are collected from EM-DAT, including the magnitude of each disaster, the number of deaths, the number of people affected, and the economic losses (also the corresponding year's CPI) caused by the disaster. In addition to the records on common disasters, the influence of COVID-19 is also considered, and the relevant data on infections (regarded as affected) and deaths are collected from the World Health Organization. Meanwhile, five macro-indicators are considered, involving GDP, population, consumer price index, arable land, and territorial areas. The macro-indicator data (excluding CPI) of related B&R countries are collected from the World Development Indicators of World Bank Open Data. Data in two predefined time intervals, i.e., 1989–2012 and 1989–2021, are grouped to compare the national resilience changes before and after the B&R initiative.

The collected original data are pre-processed by the manual data supplementations and adjustments to eliminate the incompleteness and inconsistence. Based on the pre-processed disaster data and macro-indicator data, the initial information on losses from three perspectives, i.e., the number of deaths, the number of people affected, and the economic losses, were quantified.[1]

3.2.2. Notations

In this paper, M disasters and N countries are considered, $M, N \in \mathbb{N}^+$, and their corresponding lowercase letters (m and n) are used to denote one specific disaster and country, respectively. $\mathscr{D}$, $\mathscr{A}$, and $\mathscr{E}$ denote death dimension, affected dimension, and economic dimension, respectively. All notations used to represent the current problem on national resilience assessment are provided below.

$L_n^{\mathscr{D}}$: The actual number of deaths in the n th country caused by all M disasters.

$L_n^{\mathscr{A}}$: The actual number of people affected in the n th country caused by all M disasters.

$L_n^{\mathscr{E}}$: The actual economic loss in the n th country caused by all M disasters.

$EL_n^{\mathscr{D}}$: The estimated number of deaths in the n th country caused by all M disasters.

$EL_n^{\mathscr{A}}$: The estimated number of people affected in the n th country caused by all M disasters.

$EL_n^{\mathscr{E}}$: The estimated economic loss in the n th country caused by all M disasters.

[1] The original data will be made available on request.

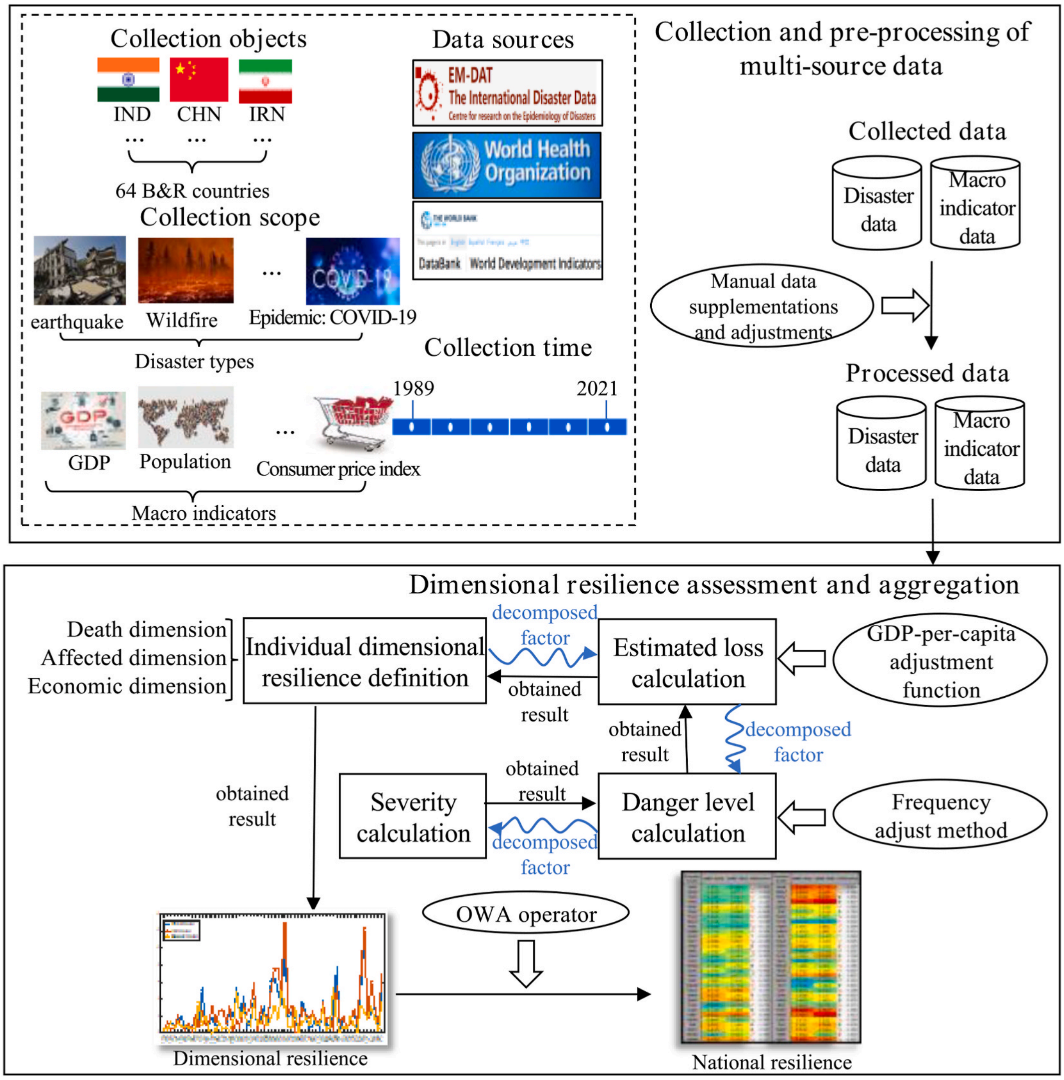

Fig. 1. Conceptual framework for national resilience assessment.

- *Collection and pre-processing of multi-source data.* The main tasks in this part include determining the collection objects (i.e., sample countries), collection scope (i.e., related disaster types and macro-indicators), data sources, and collection time. Based on the analysis of existing studies and actual requirements, as well as the consideration of data availability, the B&R sample countries, specific disaster types and macro-indicators are determined, and the related data from 1989 to 2021 are collected from the EM-DAT, World Health Organization, and World Development Indicators of World Bank Open Data. Subsequently, these collected multi-source data are pre-processed to eliminate the incompleteness and inconsistence of original data. Regarding the individual incomplete data, the specific data supplementations are conducted by a manual way. For example, the data related to the special administrative regions are supplemented to their corresponding sovereign country manually. Regarding the individual inconsistent data, some specific data adjustments are carried out by a manual way. For example, taking the value of consumer price index (CPI) in 2019 as the benchmark, the CPI values of other years are adjusted manually. Moreover, the data between different original data files are adjusted to be aligned.
- *Dimensional resilience calculation and aggregation.* Four tasks are involved in dimensional resilience calculation, i.e., individual dimensional resilience definition, estimated loss calculation, danger level calculation, and severity calculation. The calculation of dimensional resilience is a double-oriented process. Specifically, the clockwise process is a logic-oriented one that shows how we decompose the defined dimensional resilience to computable underlying factor (i.e., severity) layer by layer, while the counter-clockwise process is a result-oriented one that shows how we embed the obtain calculation results of severity to the calculation of danger level, subsequently to that of estimated loss, and finally to that of dimensional resilience. In this part, GDP per capita adjustment function and frequency adjustment method are proposed to support the estimated loss calculation and danger level calculation, respectively. After calculating the dimensional resilience, the ordered weighted average (OWA) operator [34] is used to aggregate the three-dimensional resilience results into the national resilience.

$\mathscr{R}_n^{\mathscr{D}}$: The national resilience of the n th country on the death dimension.
$\mathscr{R}_n^{\mathscr{A}}$: The national resilience of the n th country on the affected dimension.
$\mathscr{R}_n^{\mathscr{E}}$: The national resilience of the n th country on the economic dimension.
$\mathscr{R}_n$: The aggregated national resilience of the n th country.

3.3. Dimensional resilience calculation

3.3.1. Individual dimensional resilience definition

The death, affected, and economic dimensions are the most critical indices in measuring the loss severity caused by disasters. Based on the work of Zhang and Huang [27], the resilience of the n th country in each dimension can be defined as the ratio of expected loss to actual loss, i.e.,

$$\mathscr{R}_n^{\mathscr{D}} = \frac{EL_n^{\mathscr{D}}}{L_n^{\mathscr{D}}}, \forall n \in \{1, 2, \ldots, N\}, \tag{1a}$$

$$\mathscr{R}_n^{\mathscr{A}} = \frac{EL_n^{\mathscr{A}}}{L_n^{\mathscr{A}}}, \forall n \in \{1, 2, \ldots, N\}, \tag{1b}$$

$$\mathscr{R}_n^{\mathscr{E}} = \frac{EL_n^{\mathscr{E}}}{L_n^{\mathscr{E}}}, \forall n \in \{1, 2, \ldots, N\}. \tag{1c}$$

Note that the actual number of deaths $L_n^{\mathscr{D}}$, the actual number of people affected $L_n^{\mathscr{A}}$, and the actual economic loss $L_n^{\mathscr{E}}$ are available in the EM-DAT and World Health Organization.

3.3.2. Estimated loss calculation

The estimated losses can be regarded as the product of the scalar and the corresponding danger level [27]. For death and affected dimensions, physiological density is employed as the scalar. For economic dimension, considering that some B&R countries are experiencing poor economic development, an adjustment function of GDP per capita is presented as the scalar to eliminate the differences in economic volume among countries. According to **Corollary A1** (see **Appendix A**), the adjustment function of GDP per capita $f(GDPc_n)$ is defined as follows,

$$f(x) = \begin{cases} 5x^3 - 6x^2 + 2x, 0 \le x \le 0.6791 \text{ (units : \$10,000)}, \\ (x - x') + \left[5(x')^3 - 6(x')^2 + 2(x')\right], x > 0.6791 \text{ (units : \$10,000)}. \end{cases} \tag{2}$$

The GDP per capita adjustment function is depicted in Fig. 2.

Thus, the estimated losses can be calculated by the following equation.

$$EL_n^{\mathscr{D}} = D_n^{\mathscr{D}} \times PD_n, \forall n \in \{1, 2, \ldots, N\}, \tag{3a}$$

$$EL_n^{\mathscr{A}} = D_n^{\mathscr{A}} \times PD_n, \forall n \in \{1, 2, \ldots, N\}, \tag{3b}$$

$$EL_n^{\mathscr{E}} = D_n^{\mathscr{E}} \times f(GDPc_n), \forall n \in \{1, 2, \ldots, N\}, \tag{3c}$$

where PD_n is the physiological density of the n th country; $D_n^{\mathscr{D}}$, $D_n^{\mathscr{A}}$, and $D_n^{\mathscr{E}}$ are the danger levels of the n th country on death, affected, and economic dimensions, respectively.

Note: The partial view within the whole figure is a locally enlarged image, which is zoomed in on the interval of 0–68% of the highest GDP per capita ($8311).

3.3.3. Danger level calculation

To calculate the estimated losses in Equation (3), the danger level of the disasters needed to be calculated. Scholars in existing

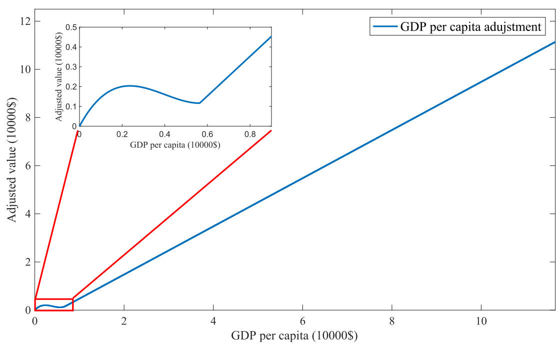

Fig. 2. GDP per capita adjustment function.

studies regarded the danger level as the product of the severity and frequency of disasters, while ignored the influence of disaster magnitude [27]. Motivated by the relationship between earthquake magnitude and earthquake energy, the relationship between disaster magnitude and its frequency are constructed.

Richter [35] identified the following relationship between earthquake magnitude and earthquake energy:

$$\lg(Ene) = 4.8 + 1.5 \times Mag \tag{4}$$

where $\lg(\cdot)$ denotes the logarithmic function with a base of 10, *Mag* and *Ene* denote earthquake magnitude and earthquake energy, respectively. According to Equation (4), the earthquake energy increases by a factor of 31.6 for a one-unit increase in magnitude.

Assumption 1. Based on the relationship between earthquake energy and earthquake magnitude, we assume that the damage caused by an earthquake increases by approximately 31.6 times for a one-unit increase in magnitude.

Definition of adjusted disaster times: According to the **Assumption 1** and the calculation method of Global terrorism index [36], the adjusted disaster times are defined as an exponential function of magnitude,

$$AdjT = e^{\alpha \times \frac{Mag - Sta}{Max - Sta}} \tag{5}$$

where AdjT denotes the adjusted times, which represents how many times an earthquake with a specific magnitude is equivalent to an earthquake with a standard magnitude; Max represents the maximum earthquake magnitude value that occurred in the record and is equal to 9; and Sta denotes the standard earthquake magnitude value. Because earthquakes below magnitude 4 often do not cause disasters, we use magnitude 5 as the standard earthquake magnitude, namely, $\mathrm{Sta} = 5$. Based on the above parameters setting and **Assumption 1**, the AdjT of $\mathrm{Mag} = \mathrm{i} + 1$ should be 31.6 times of hat of $\mathrm{Mag} = \mathrm{i}$. Accordingly, α ($\alpha \in \mathbb{R}^+$) then become a constant, 13.82.

Based on Equation (5), the adjusted frequency can be defined as

$$\mathrm{Adj}\mathscr{F}_n^m = \sum_{f=1}^{\mathscr{F}_n^m} AdjT_n^{m,f} \tag{6}$$

where $\mathrm{Adj}\mathscr{F}_n^m$ denotes the adjusted frequency of disaster *m* occurring in country *n*, and $AdjT_n^{m,f}$ denotes the adjusted times for the *f* th disaster of disaster *m* occurring in country *n*. Accordingly, the total adjusted frequency of disaster *m* that occurred in all B&R countries can be calculated by

$$\mathrm{Adj}\mathscr{F}^m = \sum_{n=1}^{N} \mathrm{Adj}\mathscr{F}_n^m \tag{7}$$

in order to adjust other disaster frequency, the frequency adjustment method of earthquakes is mapped to other disasters based on statistical information. Table 1 shows the global frequency of all earthquakes from 1900 to 2021. By mapping the quantile of the magnitude value of other disasters to the frequency information on earthquakes, the frequency of other disasters could be adjusted in the same way as earthquake disasters. Taking drought disaster as an example, if the drought-affected area is greater than 86.55% of the historical drought disaster, the drought disaster is classified as a level 8 disaster, and then the adjusted disaster frequency can be calculated by using Equation (6).

By comparing the magnitude values of other disasters with earthquake magnitude, Equations (5) and (6) can be also used to adjust the frequency of other disasters. Based on the relationship between disaster magnitude and its frequency, the original frequency information and embedded disaster magnitude information into our model are adjusted. Thus, danger levels can be defined as

$$D_n^{\mathscr{D}} = \sum_{m=1}^{M} \mathrm{Adj}\mathscr{F}_n^m \times S^{\mathscr{D},m}, \forall n \in \{1, 2, \ldots, N\}, \tag{8a}$$

$$D_n^{\mathscr{A}} = \sum_{m=1}^{M} \mathrm{Adj}\mathscr{F}_n^m \times S^{\mathscr{A},m}, \forall n \in \{1, 2, \ldots, N\}, \tag{8b}$$

$$D_n^{\mathscr{E}} = \sum_{m=1}^{M} \mathrm{Adj}\mathscr{F}_n^m \times S^{\mathscr{E},m}, \forall n \in \{1, 2, \ldots, N\}, \tag{8c}$$

Table 1
Statistical analysis of earthquake magnitude values.

Magnitude	Frequency	Percentage (%)	Cumulative percentage (%)
≤ 4	24	1.66%	1.66%
5	244	16.83%	18.48%
6	527	36.34%	54.83%
7	460	31.72%	86.55%
≥ 8	195	13.45%	100.00%
Total	1450	100%	–

where $S^{\mathscr{D},m}$, $S^{\mathscr{A},m}$, and $S^{\mathscr{E},m}$ are the severity of disaster m on death, affected, and economic dimensions, respectively.

3.3.4. Severity calculation

In Equation (8), the severity of disaster m can be calculated as the weighted average of each country's severity when facing disaster m, where the weight is the comparative disaster frequency. Then, the severity of disaster m on each dimension can be defined as

$$S^{\mathscr{D},m} = \sum_{n=1}^{N} \frac{\mathrm{Adj}\mathscr{F}_n^m}{\mathrm{Adj}\mathscr{F}^m} \times S_n^{\mathscr{D},m}, \forall m \in \{1,2,\ldots,M\}, \tag{9a}$$

$$S^{\mathscr{A},m} = \sum_{n=1}^{N} \frac{\mathrm{Adj}\mathscr{F}_n^m}{\mathrm{Adj}\mathscr{F}^m} \times S_n^{\mathscr{A},m}, \forall m \in \{1,2,\ldots,M\}, \tag{9b}$$

$$S^{\mathscr{E},m} = \sum_{n=1}^{N} \frac{\mathrm{Adj}\mathscr{F}_n^m}{\mathrm{Adj}\mathscr{F}^m} \times S_n^{\mathscr{E},m}, \forall m \in \{1,2,\ldots,M\}, \tag{9c}$$

where $S_n^{\mathscr{D},m}$, $S_n^{\mathscr{A},m}$, and $S_n^{\mathscr{E},m}$ are the severity of the m th disaster in the n th country on death, affected, and economic dimensions, respectively. Inspired by the work of Zhang and Huang [27], $S_n^{\mathscr{D},m}$, $S_n^{\mathscr{A},m}$, and $S_n^{\mathscr{E},m}$ can be defined as

$$S_n^{\mathscr{D},m} = \frac{L_n^{\mathscr{D},m}}{\mathrm{Adj}\mathscr{F}_n^m \times PD_n}, \forall n \in \{1,2,\ldots,N\}, m \in \{1,2,\ldots,M\}, \tag{10a}$$

$$S_n^{\mathscr{A},m} = \frac{L_n^{\mathscr{A},m}}{\mathrm{Adj}\mathscr{F}_n^m \times PD_n}, \forall n \in \{1,2,\ldots,N\}, m \in \{1,2,\ldots,M\}, \tag{10b}$$

$$S_n^{\mathscr{E},m} = \frac{L_n^{\mathscr{E},m}}{\mathrm{Adj}\mathscr{F}_n^m \times f(GDPc_n)}, \forall n \in \{1,2,\ldots,N\}, m \in \{1,2,\ldots,M\}. \tag{10c}$$

Based on the above setting and combining with Equations (1) – (10), the resilience of the n th country on each dimension can be obtained, namely,

$$\mathscr{R}_n^{\mathscr{D}} = \frac{PD_n \times \left[\sum_{m=1}^{M} \mathrm{Adj}\mathscr{F}_n^m \times \left(\sum_{n=1}^{N} \frac{L_n^{\mathscr{D},m}}{\mathrm{Adj}\mathscr{F}^m \times PD_n}\right)\right]}{L_n^{\mathscr{D}}}, \forall n \in \{1,2,\ldots,N\}, \tag{11a}$$

$$\mathscr{R}_n^{\mathscr{A}} = \frac{PD_n \times \left[\sum_{m=1}^{M} \mathrm{Adj}\mathscr{F}_n^m \times \left(\sum_{n=1}^{N} \frac{L_n^{\mathscr{A},m}}{\mathrm{Adj}\mathscr{F}^m \times PD_n}\right)\right]}{L_n^{\mathscr{A}}}, \forall n \in \{1,2,\ldots,N\}, \tag{11b}$$

$$\mathscr{R}_n^{\mathscr{E}} = \frac{f(GDPc_n) \times \left[\sum_{m=1}^{M} \mathrm{Adj}\mathscr{F}_n^m \times \left(\sum_{n=1}^{N} \frac{L_n^{\mathscr{E},m}}{\mathrm{Adj}\mathscr{F}^m \times f(GDPc_n)}\right)\right]}{L_n^{\mathscr{E}}}, \forall n \in \{1,2,\ldots,N\}, \tag{11c}$$

where $L_n^{\mathscr{D},m}$ denotes the actual number of deaths of the n th country by disaster m, $L_n^{\mathscr{A},m}$ denotes the actual number of affected of the n th country by disaster m, and $L_n^{\mathscr{E},m}$ denotes the actual economic loss of the n th country by disaster m.

Proposition 1. *For the death and affected dimensional resilience, in the case of the same deaths or affected: 1) the higher the adjusted frequency ($\sum_{m=1}^{M}\mathrm{Adj}\mathscr{F}_n^m$) of one country, the higher its death or affected dimensional resilience; 2) the higher the physiological density (PD_n) of one country, the higher its death or affected dimensional resilience.*

Proposition 2. *For the economic dimensional resilience, in the case of the same economic loss: 1) the higher the adjusted frequency ($\sum_{m=1}^{M}\mathrm{Adj}\mathscr{F}_n^m$) of one country, the higher its economic dimensional resilience; 2) the higher the adjusted GDP* per capita *($f(GDPc_n)$) of one country, the higher its economic dimensional resilience.*

The proof of **Propositions 1** *and* **2** *are provided in* **Appendix B**.

3.4. Resilience aggregation

Due to natural and geographical reasons, a few countries had a very high frequency of natural disasters, while other countries experienced very few natural disasters, if not no natural disasters. Therefore, the national resilience is clearly clustered on two end-points, making it a challenge to properly differentiate one country's resilience from that of another. In view of this, the logarithmic method with a base e is used to better differentiate resilience, see Equation (12).

$$\mathscr{R}_n^{\mathscr{D}'} = \ln\left(1 + \mathscr{R}_n^{\mathscr{D}}\right), \forall n \in \{1,2,\ldots,N\}, \tag{12a}$$

$$\mathscr{R}_n^{\mathscr{A}'} = \ln\left(1 + \mathscr{R}_n^{\mathscr{A}}\right), \forall n \in \{1, 2, \dots, N\}, \tag{12b}$$

$$\mathscr{R}_n^{\mathscr{E}'} = \ln\left(1 + \mathscr{R}_n^{\mathscr{E}}\right), \forall n \in \{1, 2, \dots, N\}, \tag{12c}$$

where $\mathscr{R}_n^{\mathscr{D}'}$, $\mathscr{R}_n^{\mathscr{A}'}$, and $\mathscr{R}_n^{\mathscr{E}'}$ are the revised death resilience, affected resilience, and economic resilience, respectively.

Subsequently, the three-dimensional resilience can be aggregated through the OWA operator, namely,

$$\mathscr{R}_n = OWA_{(\omega_1,\omega_2,\omega_3)}\left(\mathscr{R}_n^{\mathscr{D}'}, \mathscr{R}_n^{\mathscr{A}'}, \mathscr{R}_n^{\mathscr{E}'}\right) = \sum_{j=1}^{3} \omega_j b_j, \forall n \in \{1, 2, \dots, N\}, \tag{13}$$

where $(\omega_1, \omega_2, \omega_3)$ denotes the weight vector, and b_j is the j th maximum component of $\{\mathscr{R}_n^{\mathscr{D}'}, \mathscr{R}_n^{\mathscr{A}'}, \mathscr{R}_n^{\mathscr{E}'}\}$. The detailed process of determination of weight vector is shown in **Appendix C**.

4. National resilience assessment results

In this section, the obtained assessment results are analyzed from multiple perspectives to clarify the national resilience profile of 64 B&R countries.

4.1. National resilience overview

Based on the quantified multi-source data, the national resilience of 64 B&R countries was calculated using the proposed assessment model. The national resilience of each country in each predefined time interval as well as their changes between these time intervals were shown in Table 2. Intuitively, either in the 1989–2012 or 1989–2021 period, only a small number of values were greater than 3 (i.e., one-half of the maximum resilience value), which indicated that the general national resilience of B&R countries was low. The average value of "Difference" for national resilience was −0.001, indicating that the national resilience decreased slightly overall. Additionally, the arrow denoting 'Difference' indicates that the national resilience of most B&R countries did not exhibit an improvement after the B&R initiative. Specifically, 11 countries obtained ↑, 14 countries obtained ↗, 13 countries obtained →, 18 countries obtained ↘, and 8 countries obtained ↓. Only 25 countries experienced an increase in national resilience. Overall, the national resilience of B&R countries was relatively low, and the national resilience of these countries has not significantly improved since the B&R Initiative was proposed.

The national resilience of each B&R country in Table 2 is the aggregated value combining death resilience, affected resilience, and economic resilience. To test the reasonability of aggregating the three resilience dimensions to national resilience, the ANOVA method was introduced in this study. ANOVA was used to measure the similarity of observations from different dimensions (see Table 3).

As shown in Table 3, when a 90% confidence level was considered, the ANOVA results in the periods 1989–2012 and 1989–2021 both rejected the original hypothesis (H_0: $\mu_1 = \mu_2 = \mu_3$). That is, the death resilience, affected resilience, and economic resilience were statistically not same. Thus, using only one of the dimensions to represent national resilience would yield a biased result, while assessing national resilience from three dimensions could make it more scientific and reasonable.

4.2. Individual dimensional resilience

Analyzing each dimensional resilience is beneficial for countries to clarify which dimension they were weak in and then take targeted measures for resilience improvement. Equation (11) was used to obtain dimensional resilience values of each B&R country (see Fig. 3). Overall, the resilience dimensions exhibit a synchronized trend.

According to the comparisons between each dimensional resilience and the corresponding dimensional average resilience, 64 B&R countries could be divided into three grades.

- *Excellent* grade, i.e., the country achieved high resilience values in all three dimensions compared to the average level, e.g., Singapore (SGP) and Bahrain (BHR).
- *Fair* grade, i.e., the country achieved high resilience values in one or two of the three dimensions but performed poorly in the rest. For example, Kazakhstan (KAZ) had higher economic resilience than the average level, while its death and affected resilience dimensions did not.
- *Poor* grade, i.e., the country performed worse in all three dimensions than the average level, e.g., Pakistan (PAK) and Ukraine (UKR).

Resilience rating is beneficial for these B&R countries to develop a step-by-step and phased resilience improvement strategy that suit to its own situation. Specifically, for countries with *Poor* grades, a short-term resilience improvement strategy should be developed to allocate limited resources to quickly improve the most critical dimension; for countries with the *Fair* grade, a focused resilience improvement strategy should be developed to improve the weaker dimension(s); for countries with an *Excellent* grade, a sustainable resilience improvement strategy should be developed to maintain its comparative advantages.

4.3. Resilience change with time

For each country, "Difference" in Table 2 indicates how the national resilience changed over time. Using a similar calculation, the differences in death resilience, affected resilience, and economic resilience were also obtained. By decomposing the "Difference" in

Table 2
National resilience assessment results of each country.

Country code	1989-2012	1989-2021	Difference	Country code	1989-2012	1989-2021	Difference
IND	0.551	0.349	-0.202	BHR	5.184	4.776	-0.408
CHN	0.620	0.670	0.050	MDV	3.614	3.446	-0.168
IRN	0.535	0.533	-0.002	BTN	3.159	4.015	0.856
PAK	0.418	0.545	0.127	SGP	5.761	6.698	0.937
PHL	1.559	1.371	-0.188	GEO	1.312	1.229	-0.083
IDN	0.916	0.848	-0.068	TJK	0.675	1.438	0.763
TUR	0.531	0.446	-0.085	RUS	1.167	0.925	-0.242
BGD	0.568	0.617	0.049	UKR	0.119	0.150	0.032
POL	0.448	0.333	-0.115	YEM	1.457	1.851	0.394
VNM	0.740	0.904	0.164	ARM	1.450	1.881	0.431
AFG	1.105	1.066	-0.040	AZE	0.866	0.949	0.083
EGY	2.086	1.897	-0.189	KGZ	1.314	1.340	0.025
IRQ	1.731	1.169	-0.562	HRV	2.352	1.228	-1.124
NPL	1.165	0.707	-0.458	LTU	0.403	0.758	0.355
LBN	0.648	0.948	0.300	UZB	2.050	3.184	1.134
LKA	0.437	0.613	0.176	BLR	0.338	0.500	0.162
MNG	0.730	1.232	0.502	MKD	1.086	0.901	-0.185
ALB	1.072	0.606	-0.466	KAZ	1.452	1.445	-0.007
THA	0.438	0.677	0.239	TKM	3.147	3.985	0.837
JOR	1.582	1.319	-0.263	MDA	0.156	0.266	0.110
MMR	0.714	0.759	0.045	EST	0.298	1.099	0.801
SAU	2.413	2.888	0.475	CZE	0.603	0.494	-0.109
BGR	3.103	1.281	-1.822	SVK	1.826	1.217	-0.610
MYS	2.934	2.884	-0.050	SVN	0.885	1.460	0.575
SYR	0.202	0.476	0.274	BIH	0.646	0.475	-0.171
LAO	0.743	1.389	0.646	KWT	5.683	4.302	-1.380
ARE	3.655	4.041	0.386	BRN	4.307	6.720	2.413
HUN	0.947	0.548	-0.399	LVA	1.675	1.511	-0.164
ISR	2.622	1.285	-1.337	TLS	2.347	2.926	0.578
ROU	2.420	1.473	-0.947	MNE	2.515	2.330	-0.184
KHM	0.507	0.991	0.484	SRB	2.302	0.684	-1.618
OMN	3.442	3.115	-0.327	QAT	4.886	4.389	-0.497

Note: 1. To distinguish the national resilience more clearly, each resilience value was matched with a different shading color. The redder (warmer) the shading color, the higher the resilience, and the bluer (cooler) the shading color, the lower the resilience. **2**. 'Difference' is the value of the national resilience in the period 1989–2021 minus that in the period 1989–2012.**3**. The direction of the arrow was set by the following rule: a difference greater than or equal to 0.5 indicates a sharp increase and is marked by ; a difference greater than or equal to 0.1 but less than 0.5 indicates a slight increase and is marked as by ; a difference greater than or equal to −0.1 but less than 0.1 indicates a very small change and is marked by ; a difference greater than or equal to −0.5 but less than −0.1 indicates a slight decrease and is marked by ; and a difference less than −0.5 indicates a sharp decrease and is marked by .

national resilience into the death, affected, and economic dimensions, it can be found that "Difference" varies considerably across dimensions. Specifically, the average values of "Difference" in death resilience, affected resilience, and economic resilience were 0.538, −0.520, and −0.265, respectively. This indicates that with the B&R construction, death resilience improved while affected

Table 3
ANOVA results in the periods 1989–2012 and 1989–2021.

ANOVA result in the period 1989–2012		ANOVA result in the period 1989–2021	
Source	SS df MS F Prob > F	Source	SS df MS F Prob > F
Columns	23.4 2 11.7 2.49 **0.086***	Columns	42.7 2 21.3 4.65 **0.011****
Error	889.8189 4.7	Error	866.6189 4.6
Total	913.2191	Total	909.2191

Note: ** indicates that pairs of means were significantly different at a confidence level of 90%, and ** indicates that pairs of means were significantly different at a confidence level of 95%.*

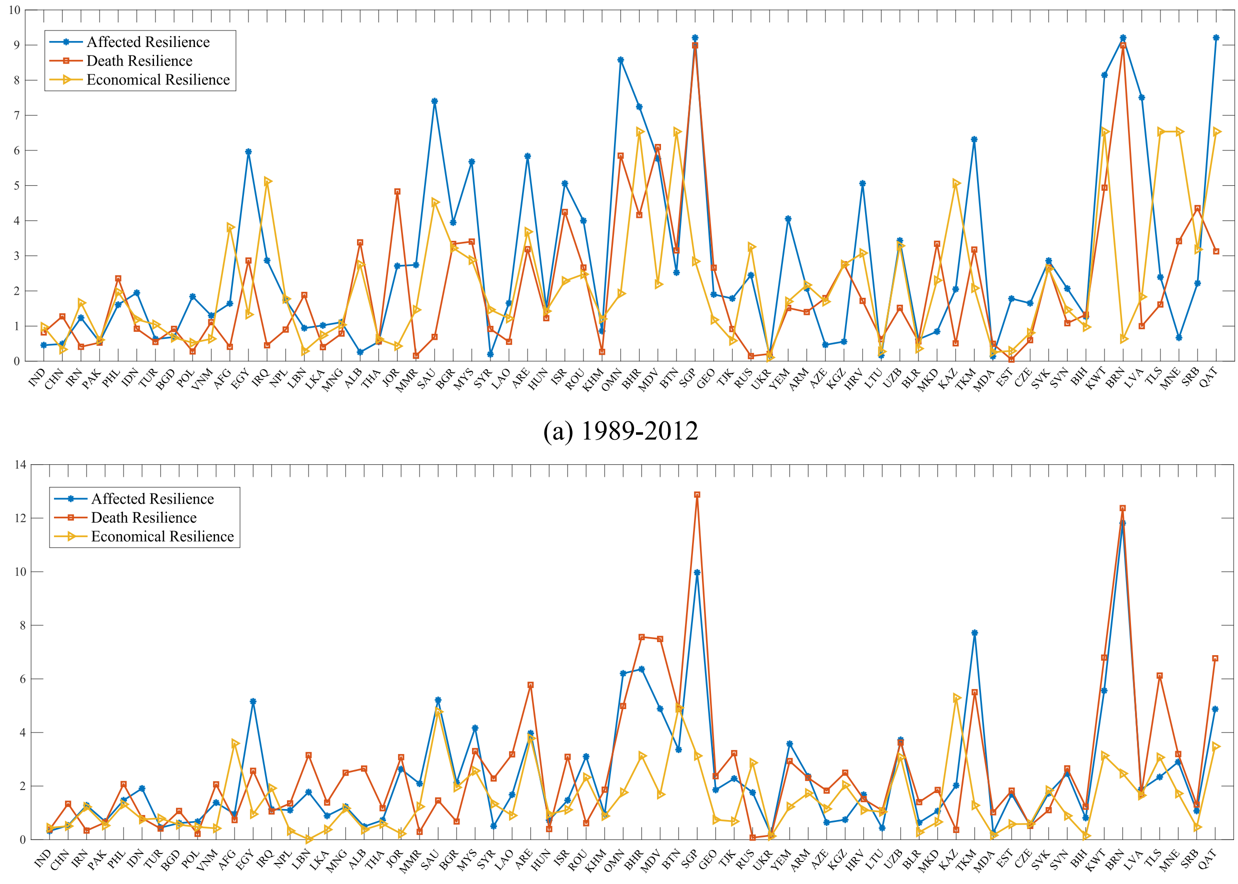

Fig. 3. Three-dimensional resilience values of each B&R country.

resilience and economic resilience worsened. The reasons are as follows: On the one hand, the massive construction of various infrastructure projects in B&R countries significantly improved their infrastructure quality, causing the number of deaths in disasters to decrease. And the number of people affected may increase because of saving from death. On the other hand, the current economic development of most B&R countries was extensive, making their economic resilience decline.

Furthermore, by using data on "Difference" in national and dimensional resilience, how the resilience changes with the implementation and construction of the B&R Initiative can be depicted in Fig. 4.

For each country, the direction of change in "Difference" generally differs across dimensions; for each resilience dimension, "Difference" fluctuates around the zero line, with mostly similar sample points above and below zero. Specifically, 31, 37, 27, and 37 B&R countries experience a positive "Difference" for national resilience, death resilience, affected resilience, and economic resilience, respectively. In other words, approximately one-half of B&R countries did not experience resilience growth despite that the construction of the B&R proceeded very well from 2013 to 2021. Thus, how to improve national resilience remains an urgent question.

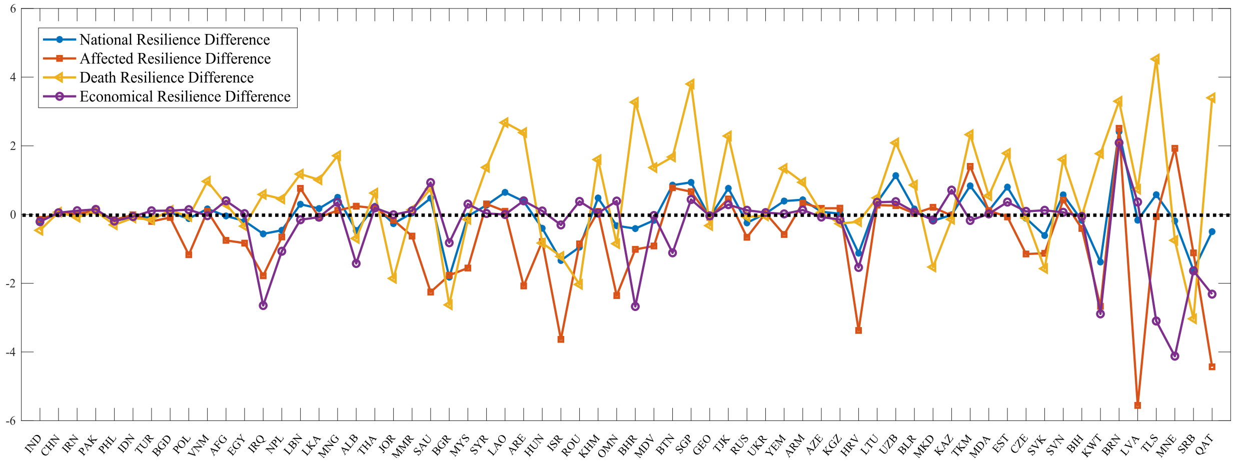

Fig. 4. Resilience changes between the periods 1989–2012 and 1989–2021. **Note:** The black dotted line is a zero line, which denotes the benchmark.

5. Resilience improvement solutions

In this section, a coefficient-adjusted stepwise regression model is developed to explore the applicable solutions for national resilience improvement. Firstly, regressors and their correlation analysis are described. Subsequently, the obtained stepwise regression results are shown. Furthermore, the detail of coefficient adjustment in the developed model is elaborated and the adjusted stepwise regression results are analyzed.

5.1. Regressors and correlation analysis

Based on the concept of national resilience, existing studies on resilience improvement are reviewed. Following the principles of systematicity, scientificity, representativeness, and accessibility, 20 macro-indicator regressors are selected from economic, institutional, and social aspects (see Table D1 in **Appendix D**). Data on these regressors are collected from the World Development Indicators of World Bank Open Data, the U.S. Census, the United Nations Educational, Scientific and Cultural Organization, and the International Telecommunications Union. In the resilience improvement analysis, 63 B&R countries[2] are considered. To reasonably calculate and compare different types of data, the data need to be standardized before use. The most common data standardization equation in the literature is min-max standardization, i.e.,

$$Value' = \frac{Value - min}{max - min}, \tag{14}$$

where $Value'$ represents the standardized data; *Value* represents the original data; and *min* and *max* represent the minimum and maximum among all observations.

Given that multiple regression is prone to the problem of serious multicollinearity [37,38], conducting a correlation analysis of the regressors before regression analysis is necessary. The interrelationship between the 20 macro-indicator regressors is visually analyzed by drawing a heatmap. As shown in Fig. 5, some of regressors are highly relevant to each other. Therefore, using linear regression to identify critical factors for resilience improvement is not applicable [39].

5.2. Stepwise regression results

To avoid the problem of multicollinearity, the classic stepwise regression model is utilized to find solutions that facilitate resilience improvement, where the resilience value is regarded as the dependent variable and 20 macro-indicator regressors are regarded as the independent variables. The stepwise regression result in the period 1989–2021 with the dependent variable being national resilience is shown in Fig. 6, which contains three pieces of information. 1) the upper part depicts the coefficients of each indicator, and the variables with blue color are significant variables; 2) the middle part depicts the statistical information of the stepwise regression, which contains the intercept value, the root mean squared error (RMSE), the indices of goodness of fit, namely, R^2 and adjusted R^2, and the significant index F test result and its corresponding p value; and 3) the bottom part depicts the changes in the RMSE of each step in the stepwise regression. The detailed analysis of the stepwise regression result taking national resilience as an example is shown in **Appendix E**. Moreover, the stepwise regression results in the period 1989–2021 with the dependent variables being death resilience, affected resilience, and economic resilience are shown in Fig. F1 to Fig. F3 of **Appendix F**.

After completing the stepwise regression, the heatmaps are plotted again for the significant regressors from the perspective of national resilience and dimensional resilience (see Fig. G1 to Fig. G4 in **Appendix G**). The redrawn heatmap shows that the correlation between

[2] The Islamic Republic of Afghanistan (AFG) was omitted due to excess missing data.

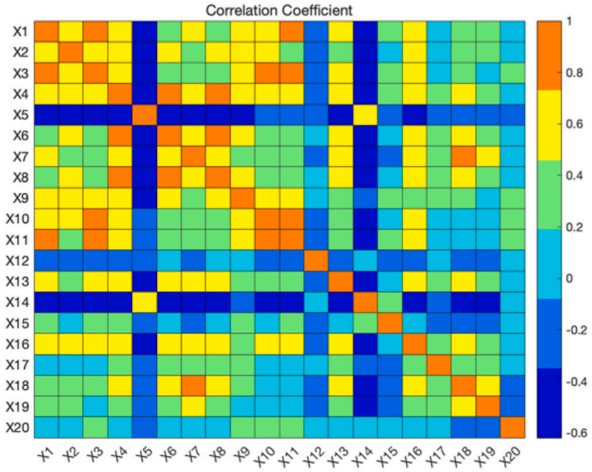

Fig. 5. Heatmap: Correlation analysis between 20 macro-indicator regressors. **Note: 1**. The warmer (redder) the color of the squares, the stronger the positive linear correlation between the two regressors. While the cooler (bluer) the color of the squares, the stronger the negative linear correlation between the two regressors; **2.** Data period: 1989–2021.

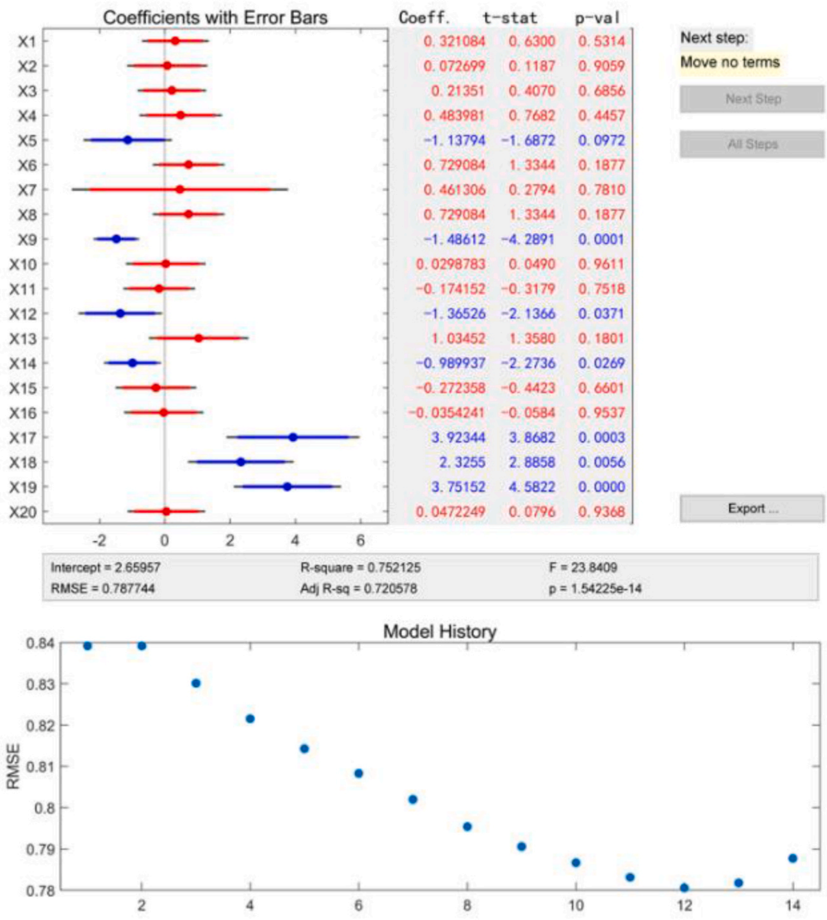

Fig. 6. Stepwise regression result with the dependent variable being national resilience.

these significant regressors decreased significantly compared to Fig. 5, which demonstrates the effectiveness of the stepwise regression.

Although Fig. 6 and Fig. F1 to Fig. F3 shown that more than half of the regressors are insignificant in the stepwise regression, these insignificant regressors may also be important for resilience improvement. How one explains these insignificant regressors also matters, since they are not unimportant but are simply replaced by other regressors in the stepwise regression. Thus, a new approach is designed to measure the effects of insignificant variables. Specifically, the coefficients of insignificant variables in the stepwise regression are calculated using the information on the correlation coefficients and significant coefficients together.

5.3. *Coefficient adjustment and adjusted stepwise regression results*

In this study, 20 macro-indicator regressors are involved. It is assumed that these regressors belonged to the set $\boldsymbol{U}$, such that $\boldsymbol{U} = \{X_1, X_2, \ldots, X_{20}\}$, and the significant regressors also belonged to $\boldsymbol{P}$, such that $\boldsymbol{P} \subseteq \boldsymbol{U}$. The components of the correlation coefficient matrix of 20 macro-indicator regressors are assumed to be $r_{i,j}$ for $i,j \in \boldsymbol{U}$. Then, by denoting C_i as the coefficient of regressor i ($i \in \boldsymbol{U}$), the coefficient of the insignificant regressor can be defined as

$$C_i = \frac{\sum_{j \in S} (C_j \times r_{i,j})}{s}, \forall i \in \boldsymbol{U} \setminus \boldsymbol{P}, \tag{15}$$

where s denotes the number of significant regressors. To explain this approach clearly, a simple but straightforward example was constructed to illustrate Equation (15), see Fig. 7.

Using Equation (15), the adjusted stepwise regression results of national resilience, death resilience, affected resilience, and economic resilience in the period 1989–2021 are obtained, see Table 4.

Note: This figure shows how to calculate the coefficients of the insignificant regressors. It is assumed that there are three regressors, and their correlation is depicted using a correlation coefficient matrix. β_1 and β_3 are assumed to be significant regressors by stepwise regression, while β_2 is an insignificant regressor. Then, β_2 can be obtained by components of the correlation coefficient matrix and coefficients of the significant regressors.

Overall, Table 4 shows that 1) X_1, X_2, X_3, and X_4 have a positive influence on resilience improvement, which indicates that increasing the ratio of access to basic sanitation, water, electricity, and the Internet is good for building a resilient country, as these regressors represent people's basic needs. 2) X_6 and X_8 are positive, which means that a noncorrupt and efficient government is also necessary for resilience improvement. 3) X_7, X_{10}, and X_{11} are positive; thus, increasing the GDP per capita and the literacy rate are also helpful for resilience improvement. 4) X_9, X_{14}, and X_{15} are negative because employment provides individuals with a livelihood, while unemployment deprives people of the ability to cope with disasters. 5) X_{13} is positive, which means that good communication conditions facilitate early warning information broadcasting during emergencies. 6) X_{18} is positive, which means that air freight is helpful in ensuring rapid and timely disaster relief. 7) X_{19} is positive, which means that considering infrastructure quality corresponding to the disaster frequency in a country is necessary for resilience improvement. 8) X_{20} is negative because emergency aid is needed when a disaster breaks out, but railway freight as a substitute for air freight is usually not as fast as airplanes and is also easily influenced by various disasters, such as floods [40].

6. Comparison and discussion

In this section, a comparative analysis is conducted to discuss the differences of studies for national resilience assessment. Subsequently, several valuable findings regarding identified critical factors for national resilience improvement are discussed.

6.1. *Comparative analysis*

A qualitative and quantitative comparative analysis was conducted. Specifically, the qualitative comparison focused on highlighting the differences between our work and existing studies with respect to research scope and research metrics.

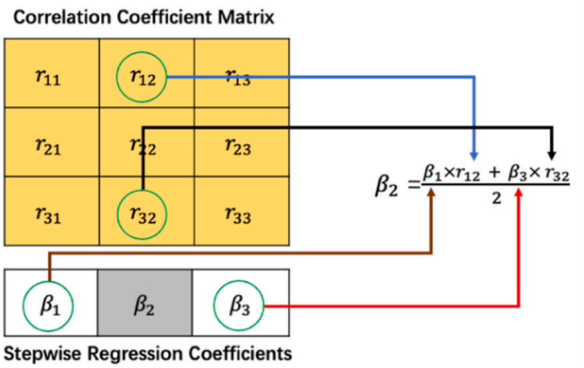

Fig. 7. Illustration of coefficient calculations for insignificant regressors.

Table 4
Regressor coefficients of each stepwise regression in the period 1989–2021.

Indicator index	National resilience	Affected resilience	Death resilience	Economic resilience
X_1	0.4124	0.3758	0.5380	0.4126
X_2	0.3443	0.3348	0.4135	0.3175
X_3	0.2533	0.2551	0.3115	0.3517
X_4	0.5795	0.5338	0.7466	0.6141
X_5	-1.493	-0.3236	-2.5204	-0.4107
X_6	0.651	0.6219	0.8643	0.4496
X_7	0.9935	0.9693	1.3393	0.7923
X_8	0.651	0.6219	0.8643	0.4496
X_9	-1.8449	-2.1548	-3.6936	-1.5314
X_{10}	0.1086	0.1229	1.6429	0.2912
X_{11}	0.0759	0.1223	0.16	0.2128
X_{12}	-1.4122	0.1399	-2.4374	-0.185
X_{13}	0.6525	0.551	0.8616	2.3169
X_{14}	-0.6825	-2.4253	-0.9231	-0.6177
X_{15}	-0.2662	-0.3457	-0.4079	-0.2521
X_{16}	0.7238	0.6819	-2.3435	0.6594
X_{17}	3.3108	5.4615	8.3578	0.3154
X_{18}	2.5351	0.9734	4.0544	3.0955
X_{19}	3.8507	7.6839	8.2631	0.6012
X_{20}	-0.2153	-0.2107	-0.3311	2.3801
Adjusted R^2	0.72398	0.64565	0.78052	0.40678

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Note: 1. Cells with yellow shading indicate that the corresponding indicator is significant in the stepwise regression. **2.** The majority of the signs of regressors are the same in each stepwise regression; however, some may have changed for various reasons such as outliers. **3.** The weights in Table 4 are mathematically obtained through stepwise regression, accordingly, they are not debated by the problem of subjectivity.

- *Research Scope.* Some scholars have only focused on the resilience of a single country, e.g., Philippines [26] and Pakistan [22]. Other scholars have focused on national resilience in countries around the world, such as Zhang and Huang [27]. The present paper focuses on countries in a specific region, namely, B&R countries. The need for resilience improvement has become more urgent, as these countries are more prone to disasters. At present, improving their national resilience is particularly important, which would assist in improving overall global resilience.
- *Research Metrics.* Existing studies can be classified into two types: 1) establishing a macro-indicator system while not involving disaster data or 2) constructing a resilience function in an integral form based on a single disaster data or in a single-dimensional ratio form based on multi-disaster data. To ensure the process of national resilience assessment more scientific and the results more reasonable, a three-dimensional resilience assessment model based on multi-source data is proposed, where more than 13,000 records involving 17 types of disasters and 5 macro-indicators are utilized.

The following quantitative comparison of our study and the work of Zhang and Huang [27] focuses on highlighting the model difference. Using data from EM-DAT between 1966 and 2015, the results obtained by our model and Zhang and Huang's model are compared (see Fig. 8).

As shown in Fig. 8, the obtained death resilience values of the two models differ slightly but present a similar trend. To clarify the model difference, the rank-biased overlap (RBO) approach [41] was used. The score of RBO takes values in the interval [0, 100%], where 0 means entirely different and 100% means identical. RBO is more reasonable than the Pearson correlation coefficient and the Kendall tau rank correlation coefficient, which was verified by a simple example (see **Example H1** in **Appendix H**).

Using the RBO approach, the similarity between the two models' results is obtained, i.e., 64.12%, which means that our model and Zhang & Huang's model were similar but not identical. The RBO score is coincident with the above analysis of Fig. 8. The reason that the two models are partly different is as follows.

- *Using physiological density instead of population density.* As most of the land in some B&R countries is desert, such as OMN and AER, in our model, population density was replaced by physiological density. When population density is replaced by physiological density, the value of the density index increases, thus the death resilience increases according to **Proposition 1.** This also explained why the resilience of OMN and AER obtained by our model was higher than Zhang & Huang's model.
- *Incorporating disaster magnitude into national resilience assessment model.* By incorporating magnitude into our model, a severe disaster record would be regarded as several standard disaster records; thus, the disaster frequency increases, thus the death resilience increases according to **Proposition 1.** This also explained why the resilience value of BRN obtained by our model was higher than that of Zhang & Huang's model, since there were usually few but high-magnitude disasters in BRN.

6.2. *Discussion*

In the following, some exciting new findings for national resilience improvement are discussed, which are also valuable for decision-makers in B&R countries.

- Proper urbanization is beneficial to national resilience improvement, while blindly expanding the scale of a city is not conducive to resilience improvement. X_5, the largest city's population ratio adjusted by GDP per capita, negatively influences resilience improvement. Namely, assembling too many individuals in the largest city is detrimental because enormous urban slums are formed when the largest city has high proportions of the population and featured low GDP per capita. Slums hamper resilience improvement [42]. However, X_{16}, representing the urban population ratio, is positive. Comparing X_{16} and X_5 indicates that urbanization is beneficial, while the benefits of urbanization diminish when one fails to consider urban carrying capacity.
- The path of simply increasing population size, and thereby physiological density, and ultimately national resilience, does not work. X_{12} represents the total population and has a negative effect, which means that overpopulation places pressure on existing

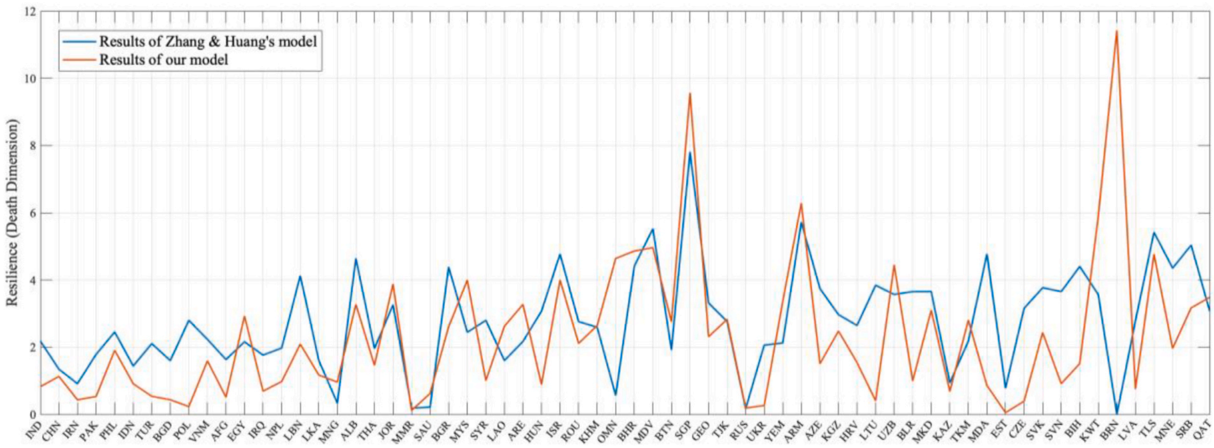

Fig. 8. Death resilience results of our model and Zhang & Huang's model.

resources and subjects more people to disasters. The indicator of physiological density (X_{17}) is positive, and GDP per capita (X_7) has the second-largest impact on X_{17} (see Fig. E1 of **Appendix E**). By comparing X_{12} and X_{17}, we could find that it is financial capacity, not the population increase, that leads to increased resilience.

Meanwhile, the considerable differences in the coefficients of each regressor (see Table 4) also indicates that using the simple average method to calculate resilience is not reasonable.

7. Conclusions

In this paper, national resilience is regarded as the comprehensive ability to avert human and economic losses caused by disasters. Accordingly, a three-dimensional national resilience assessment model based on multi-source data is proposed to clarify the national resilience of 64 B&R countries using 13,000 records involving 17 types of disasters and 5 macro-indicators. Subsequently, to explore the applicable solutions for national resilience improvement, a stepwise regression model with 20 macro-indicator regressors is developed using more than 19,000 records.

Based on the obtained assessment results and regression results, several valuable insights are discovered and discussed. Specifically, 1) evidences from the comparative analysis (Section 3.4) show that the influence of disaster magnitude, inflation, and differences in geographic landscapes are important factors for assessment national resilience; 2) the death resilience performs better than affected resilience and economic resilience. This may be because the B&R Initiative significantly improves the quality of infrastructure, dramatically decreasing the number of deaths in various disasters; 3) the national resilience of B&R countries was relatively low, and approximately one-half of these countries did not experience resilience growth despite that the B&R Initiative proceeded very well from 2013 to 2021. Thus, how to improve national resilience remains an urgent question; 4) in exploring solutions for national resilience improvement, the coefficients of 20 macro-indicator regressors are obtained, and some interesting phenomena are found. For example, an increase in the urban population ratio (X_{16}) is beneficial for national resilience improvement, but the unplanned concentration of too many people in cities without considering the economic situation (X_5) is detrimental to national resilience improvement.

To recap, this study provides quantified model support and a solution reference for national resilience assessment and improvement, which is conductive to the construction of the B&R Initiative and filling the shortfall of global national resilience. Notedly, some scholars emphasized that there were other aspects highly impact national resilience, most especially elements aspects concerning the population, such as trust in the governance systems, patriotism, etc. [43]. However, due to limitations in data characteristics as well as those in subjectivity and cognitive non-consensus to elements aspects concerning the population, these mentioned elements aspects have not yet been included in our study. In the future, with the achievement of data completeness and the formation of cognitive consensus, we will try to incorporate such elements aspects into national resilience assessment and explore several other extensions, such as quantifying the interaction among different dimensions, depicting dynamic resilience maps, and constructing intelligent and integrated systems. These would be beneficial to improving the accuracy of national resilience assessment, intuitive representation of national resilience profiles, and intellectualization of national resilience analysis.

Credit authors statement

Jianping Li: Conceptualization, Formal analysis, Writing - review & editing, Funding acquisition. **Jiaxin Yuan**: Data curation, Methodology, Investigation, Writing - original draft. **Weilan Suo**: Methodology, Validation, Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Construction the GDP per capita adjustment function

Based on an in-depth analysis of the real situation, we find that directly using the economic loss to measure economic-dimensional resilience is not suitable. The reasons are described as follows. On the one hand, economic level often reflects a country's resilience to resist disasters and avoid economic loss, while in reality the economic level of countries varies. Usually, the developed countries are more capable of acquiring and constructing risk-resistant devices to withstand various disasters, thus, they would not suffer significant economic loss from disasters. While low-income countries also would not suffer significant economic loss, even in severe disasters, because of their underdeveloped economies. Evidently, directly using the economic loss to measure economic-dimensional resilience can't reflect the differences between countries. In this instance, it is a more reasonable consideration to introduce the GDP per capital to adjust the quantification of economic loss. On the other hand, economic development mode also plays an important role in a country's resilience. It is already a consensus that the extensive development mode will destroy the environment and significantly reduce a country's ability to withstand disasters. Based on the above explanation, to accurately quantify the economic loss for the calculation of economic-dimensional resilience, with the considerations of economic level difference between countries and the influence of economic development mode, we proposed a GDP per capita adjustment function (see **Corollary A1**) according to the economic level of the economies in transition.[3]

The selection of economies in transition stems from three facts: 1) They have accumulated a certain amount of wealth, but due to the previous extensive development mode, this wealth is more vulnerable to various disasters, i.e., economic losses may be more when disasters occur; 2) Although most of the developing economies are also extensive in development, their per capita wealth usually is not as high as that of the transition economies due to their backward economy. Even if disasters occur, the losses are not too great. 3) The involved economies in transition[4] are all members of the B&R initiative.

Considering that the change of GDP per capita is a gradual process, its historical performance should be considered when adjusting. Therefore, the mean GDP per capital of each country between 1989 and 2020 is used to construct the adjustment function. According to GDP per capita data and the country list of economies in transition in *World Economic Situation and Prospects*, the upper limit of the GDP per capital is about 0.6791 (units: $10,000), which is about the 64% quantile of the world's GDP per capita. The average level is about 0.3156 (units: $10,000), which is about the 46% quantile of the world's GDP per capita.

It is well known that the richer a country is, the more able it is to withstand disasters, and the more resilient its economy should be. In order to depict the impact of extensive development on national resilience, reducing the GDP per capita of economies in transition by a certain way is a feasible alternative. In view of this, the adjusted GDP per capita should increase when GDP per capita is lower than 0.3156 (units: $10,000), decrease in the range of 0.3156 (units: $10,000) to 0.6791 (units: $10,000), and then increase when the GDP per capita is greater than 0.6791 (units: $10,000).

Assumption A1: *The GDP* per capita *adjustment function is set as a cubic function $f(x)$ when one country's GDP* per capita *is less than or equal to 0.6791 (units: $10,000), namely,*

$$f(x) = ax^3 + bx^2 + cx + d, \tag{A1}$$

where $a, b,$ *and* c are constants and x denotes the value of GDP per capita (units: $10,000).

According to **Assumption A1**, the cubic function $f(x)$ should satisfy the following two conditions: 1) $f(0) = 0$; 2) $f(x)$ has two extreme values at the points of $x = 0.3156$ and $x = 0.6791$.

Proposition A1: *When one country's GDP* per capita *is less than or equal to 0.6791 (units: $10,000), the cubic GDP* per capita *adjustment function $f(x)$ is*

$$f(x) = 5x^3 - 6x^2 + 2x, \tag{A2}$$

where $0 \le x \le 0.6791$.

Proof: According to the cubic function setting, $f(x) = ax^3 + bx^2 + cx + d$.

- *Since it requires that* $(0) = 0,\ d = 0$.
- *Since it requires that $f(x)$ is an increasing function when x is less than or equal to 0.3156 but a decreasing function when x is between 0.3156 and 0.6791, the derivative function of $f(x)$,$f'(x)$, has two roots.*

The first-order derivative of $f(x)$ is

$$f'(x) = 3ax^2 + 2bx + c. \tag{A3}$$

Based on the above two corollaries, $f'(x)$ has two roots, which means

$$\Delta = (2b)^2 - 4(3ac) > 0, \tag{A4}$$

namely, $b^2 > 3ac$.

However, $f'(x)$ has two roots under the condition of $x > 0$, which means that both roots need to be greater than 0. To satisfy this condition, the smaller root needs to be greater than 0, namely,

[3] According to the World Economic Situation and Prospects 2021 [47], countries were classified into three levels, i.e., developed economies, economies in transition, and developing economies, where the economies in transition are most vulnerable to economic losses due to the extensive development in the early stage.

[4] Economies in transition: ALB, BIH, MNE, MKD, SRB, ARM, AZE, BLR, GEO, KAZ, KGZ, MDA, RUS, TJK, TKM, UKR, UZB.

$$\frac{-2b-\sqrt{\Delta}}{6a}=\frac{-2b-\sqrt{(2b)^2-4(3ac)}}{6a}>0. \tag{A5}$$

Thus, $-b>\sqrt{b^2-3ac}>0$. Furthermore, it can be concluded that $b<0$ and $ac>0$. Since $f(x)$ is first increasing and then decreasing, it can be further obtained that $a>0$ and $c>0$. In summary, a,b,c, and d are constants, and $a>0,b<0,c>0,d=0$..

With conditions '$a>0,b<0,c>0,d=0$' and '$f(x)$ has two extreme values around the points of $x=0.3156$ and $x=0.6791$' in mind, by grid search method, the value of a,b,c, and d obtained. For simplify, a,b,c, and d are rounding to integers by design, then,

$$a=5,b<-6,c>2,d=0. \tag{A6}$$

Thus, the cubic GDP per capita adjustment function $f(x)$ when one country's GDP per capita is less than or equal to 0.6791 (units: \$10,000) of the highest GDP per capita is

$$f(x)=5x^3-6x^2+2x,0\le x\le 0.6791 \tag{A7}$$

QED.

By contrast, when the GDP per capita greater than 0.6791 (units: \$10,000), a linear function with a slope of 1 is used to directly represent the adjusted GDP per capita. To ensure the continuation at $x=0.6791$, the GDP per capita adjustment function should be cross second extreme point of the cubic in Equation (A2). Thus, when one country's GDP per capita is greater than 0.6791 (units: \$10,000), the GDP per capita adjustment function is

$$f(x)=(x-x')+\left[5(x')^3-6(x')^2+2(x')\right], \tag{A8}$$

where $x>0.6791$ of the highest GDP per capita and x' is the location of the second extreme point of Equation (A2).

Corollary A1: *The GDP* per capita *adjustment function is.*

$$f(x)=\begin{cases}5x^3-6x^2+2x,0\le x\le 0.6791,\\ (x-x')+\left[5(x')^3-6(x')^2+2(x')\right],x>0.6791.\end{cases}$$

Appendix B. Proof of Propositions 1 and 2

Proof: Proposition 1 is proved from the aspects of density index and frequency index, respectively.

(1) The increase in density will lead to an increase in dimensional resilience.

As defined in Equation (11a), the resilience of the n th country on the death dimension is

$$\mathscr{R}_n^{\mathscr{D}}=\frac{PD_n\times\left[\sum_{m=1}^{M}Adj\mathscr{F}_n^m\times\left(\sum_{n=1}^{N}\frac{L_n^{\mathscr{D},m}}{Adj\mathscr{F}^m\times PD_n}\right)\right]}{L_n^{\mathscr{D}}},\forall n\in\{1,2,\ldots,N\}.$$

Thus, the first-order derivative of $\mathscr{R}_n^{\mathscr{D}}$ on PD_n is

$$\frac{\partial\mathscr{R}_n^{\mathscr{D}}}{\partial PD_n}=\frac{\sum_{m=1}^{M}\left[\frac{Adj\mathscr{F}_n^m}{Adj\mathscr{F}^m}\times\left(\sum_{n=1}^{N}\frac{L_n^{\mathscr{D},m}}{PD_n}\right)\right]-PD_n\times\sum_{m=1}^{M}\left(\frac{Adj\mathscr{F}_n^m}{Adj\mathscr{F}^m}\times\frac{L_n^{\mathscr{D},m}}{(PD_n)^2}\right)}{L_n^{\mathscr{D}}}=\frac{\sum_{m=1}^{M}\frac{Adj\mathscr{F}_n^m}{Adj\mathscr{F}^m}\times\left[\left(\sum_{n=1}^{N}\frac{L_n^{\mathscr{D},m}}{PD_n}\right)-\frac{L_n^{\mathscr{D},m}}{PD_n}\right]}{L_n^{\mathscr{D}}}. \tag{B1}$$

Note that in Equation (B1), $Adj\mathscr{F}_n^m\ge 0$ and $\left(\sum_{n=1}^{N}\frac{L_n^{\mathscr{D},m}}{PD_n}\right)\ge\frac{L_n^{\mathscr{D},m}}{PD_n}$; thus, it was easy to conclude that $\frac{\partial\mathscr{R}_n^{\mathscr{D}}}{\partial PD_n}\ge 0$. With population density replaced by physiological density, the density index increases; thus, the resilience increases. This is true for the other two dimensions of resilience.

(2) The increase in frequency index will lead to an increase in dimensional resilience.

Based on the same idea as analyzed above, the first-order derivative of $\mathscr{R}_n^{\mathscr{D}}$ on PD_n is

$$\begin{aligned}\frac{\partial\mathscr{R}_n^{\mathscr{D}}}{\partial Adj\mathscr{F}_n^m}&=\frac{PD_n}{L_n^{\mathscr{D}}}\times\left[\left(\sum\nolimits_{n=1}^{N}\frac{L_n^{\mathscr{D},m}}{PD_n\times Adj\mathscr{F}^m}\right)-Adj\mathscr{F}_n^m\times\frac{L_n^{\mathscr{D},m}}{PD_n\times(Adj\mathscr{F}^m)^2}\right]=\frac{PD_n}{L_n^{\mathscr{D}}}\\&\times\left[\left(\sum\nolimits_{n=1}^{N}\frac{L_n^{\mathscr{D},m}\times Adj\mathscr{F}^m}{PD_n\times(Adj\mathscr{F}^m)^2}\right)-\frac{Adj\mathscr{F}_n^m\times L_n^{\mathscr{D},m}}{PD_n\times(Adj\mathscr{F}^m)^2}\right]\ge\frac{PD_n}{L_n^{\mathscr{D}}}\\&\times\left[\frac{L_n^{\mathscr{D},m}\times Adj\mathscr{F}^m}{PD_n\times(Adj\mathscr{F}^m)^2}-\frac{Adj\mathscr{F}_n^m\times L_n^{\mathscr{D},m}}{PD_n\times(Adj\mathscr{F}^m)^2}\right]=\frac{L_{\mathscr{D}_n^m}}{L_n^{\mathscr{D}}\times(Adj\mathscr{F}^m)^2}\times\left(Adj\mathscr{F}^m-Adj\mathscr{F}_n^m\right).\end{aligned} \tag{B2}$$

Note that, as defined in Equation (7),

$$Adj\mathscr{F}^m = \sum_{n=1}^{N} Adj\mathscr{F}_n^m$$

Thus, $Adj\mathscr{F}^m - Adj\mathscr{F}_n^m \geq 0$, and it was easy to conclude that $\frac{\partial \mathscr{R}_n^{\mathscr{S}}}{\partial Adj\mathscr{F}_n^m} \geq 0$, namely, resilience will increase with a frequency increase, and vice versa.

Based on the analysis of the above two aspects, we proved that the increase in density or frequency index will lead to an increase in dimensional resilience. **QED**.

Note that the proof of **Proposition 2** is similar to that of **Proposition 1** and is omitted here.

Appendix C. Determination of weight vector

Considering the "Cannikin Law", the lower resilience dimensions are expected to be given greater weight when aggregating the three-dimensional resilience. Combined with Equation (13), this implies that the elements of the weight vector $\boldsymbol{\omega}$ are incremental. Based on the work of Yager [44], the regular increasing monotone (RIM) function is used to determine the weights of the OWA operator. The RIM function is defined as

$$f(x) = x^p, p \in [0, \infty], \tag{C1}$$

where p is a constant and usually set as $p = 2$. For $p = 2$, the weight vector $\boldsymbol{\omega}$ with k attributes can be obtained by Equation (C1), such that the j th, weight is as follows:

$$\omega_j = f\left(\frac{j}{k}\right) - f\left(\frac{j-1}{k}\right) = \left(\frac{j}{k}\right)^2 - \left(\frac{j-1}{k}\right)^2 = \frac{2j-1}{k^2}, \forall j \in \{1, 2, \ldots, k\} \tag{C2}$$

In this paper, three dimensions are considered, namely, $k = 3$; thus, utilizing Equation (C2), the weight vector $\boldsymbol{\omega}$ can be obtained, namely, $\boldsymbol{\omega} = \left[\frac{1}{9}, \frac{3}{9}, \frac{5}{9}\right]$..

Appendix D. Macro-indicator regressors

The determined macro-indicator regressors for national resilience improvement are shown in Table D1.

Table D1
Macro-indicator regressor list.

Index	Indicator	Explanation
X_1	Access to basic sanitation ratio	The percentage of people with access to basic sanitation
X_2	Access to basic water ratio	The percentage of people with access to basic water
X_3	Access to electricity ratio	The percentage of people with access to electricity
X_4	Access to Internet ratio	The proportion of people who have access to the Internet in the total population
X_5	Biggest city population ratio adjusted by GDP per capita	The population of the largest city divided by the product of total population and GDP per capita
X_6	Control of corruption score	The score of the government's ability to control corruption.
X_7	GDP per capita	GDP per capita is calculated by dividing the GDP of a country by its population
X_8	Government effectiveness score	The governance ability score
X_9	Household dependency ratio	Ratio of the number of nonadults (0–14 years old) and the elderly (over 65 years old) to the number of working-age individuals (15–64 years old)
X_{10}	Literacy rate female	Measured by the percentage of females who are literate
X_{11}	Literacy rate male	Measured by the percentage of males who are literate
X_{12}	Total population	Total population
X_{13}	Mobile cellular subscriptions ratio	Mobile phone ownership rate (percentage of population)
X_{14}	Poverty rate	Percentage of people living in poverty
X_{15}	Unemployment rate	The number of people without work but actively seeking work divided by workforce population[8]
X_{16}	Urban population ratio	Proportion of urban population to total population
X_{17}	Physiological density	Measured by the population divided by arable land area
X_{18}	Air transport freight	Air freight that measured in metric tons times kilometers travelled
X_{19}	Quality of trade and transport related infrastructure considering disaster frequency	Logistics professionals' perception of country's quality of trade and transport related infrastructure, divided by disaster frequency
X_{20}	Railway freight ability	Railway freight ability measured in metric tons times kilometers travelled

Appendix E. Exemplary stepwise regression result analysis

In this study, **national resilience** serves as an example to illustrate the results obtained by stepwise regression. As depicted in the middle part of Figs. 6 and 1) the significant F test value is approximately 28.10, and its corresponding p value is very close to zero, which means that this stepwise regression is significant and effective; 2) the intercept is approximately 2.36; 3) the RMSE is approximately 0.78; and 4) regarding the goodness-of-fit index, the adjusted R^2 is approximately 0.72, which demonstrates the high explanatory ability of significant regressors.

As depicted in the upper part of Fig. 6, six variables are significant after stepwise regression, and their positive or negative signs provides valuable information to decision-makers in B&R countries. Specifically,

- X_5 denotes the largest city population ratio adjusted by the GDP per capita, which negatively affects resilience improvement. The negative sign means that the proportion of the population in the largest cities should be in line with the GDP per capita of a country. If the GDP per capita of a country is very low and too many people live in the largest cities, it is easy to form an extensive area of slums which is more fragile facing with various disasters [22].
- X_9 denotes the household dependency ratio, which negatively affects resilience improvement. Since elderly persons and children are vulnerable to various disasters, a higher X_9 indicates a larger share of elderly people and children, and hence more losses may be caused by disasters which ultimately leads to low resilience. A higher X_9 also means that a smaller share of the population participates in production and that less wealth was produced by labor, which leads to a lack of economic support to improve resilience [45].
- X_{12} denotes the total population, which negatively affects resilience improvement. Although a larger population usually means higher productivity, overpopulation may lead to more people being affected by disasters and various problems, such as poverty.
- X_{17} denotes the physiological density. The sign of X_{17} is positive, which appears to contradict X_{12} given the close relation between the total population and physiological density. Actually, the higher the physiological density is, the greater the ability of a country to support more people per unit of arable land area and to be richer. The reason is also be revealed by Fig. E1, which shows that GDP per capita (X_7) has the second-highest impact on X_{17}.

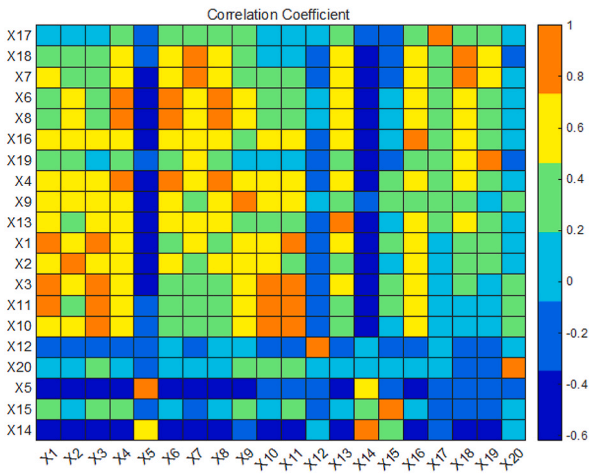

Fig. E1. Redrawn heatmap. **Note**: The vertical axis is sorted according to the correlation coefficient between X_{17} and other regressors ranked from the largest to the smallest.

- X_{18}, the air transport freight measured in metric tons times kilometers travelled, positively affects resilience improvement. A higher X_{18} indicates a greater ability to dispatch resources during emergencies and, therefore, a greater ability to respond to disasters [46].
- X_{19} denotes the quality of trade and transport-related infrastructure considering disaster frequency. The positive sign indicates that the infrastructure quality of a country should be coincident with disaster frequency.

Appendix F. Dimensional stepwise regression results

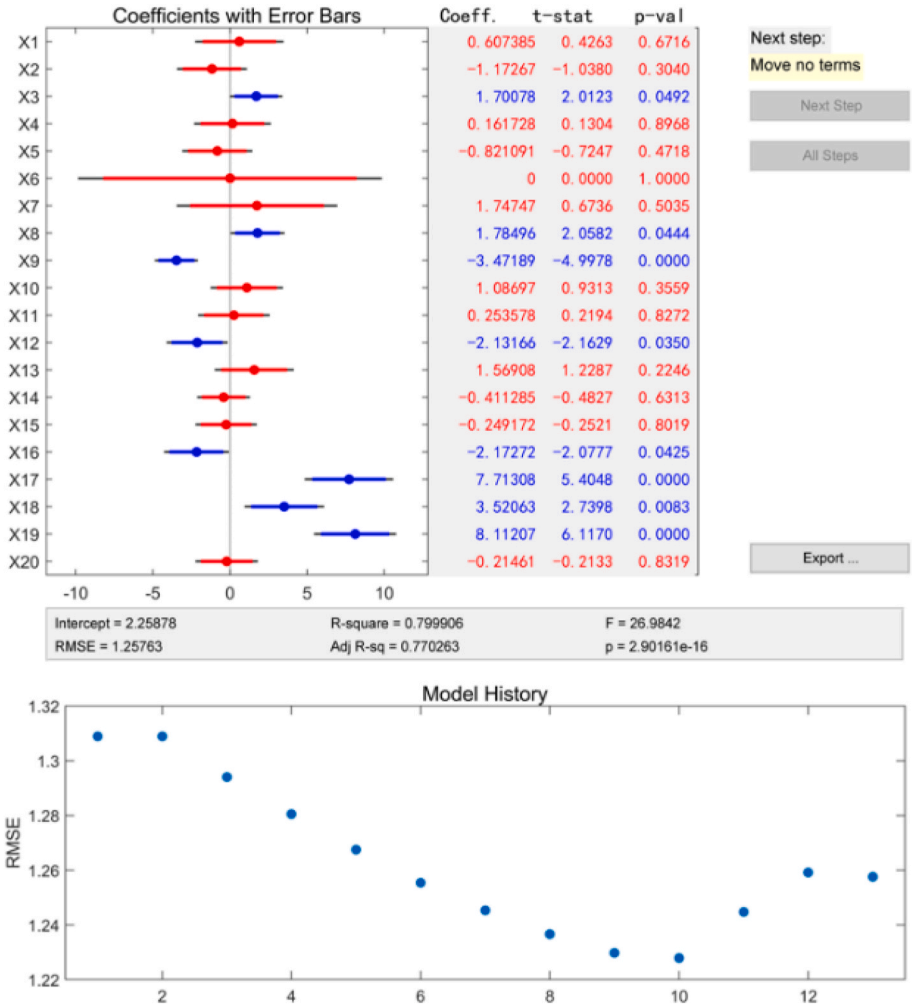

Fig. F1. Stepwise regression result with the dependent variable being death resilience.

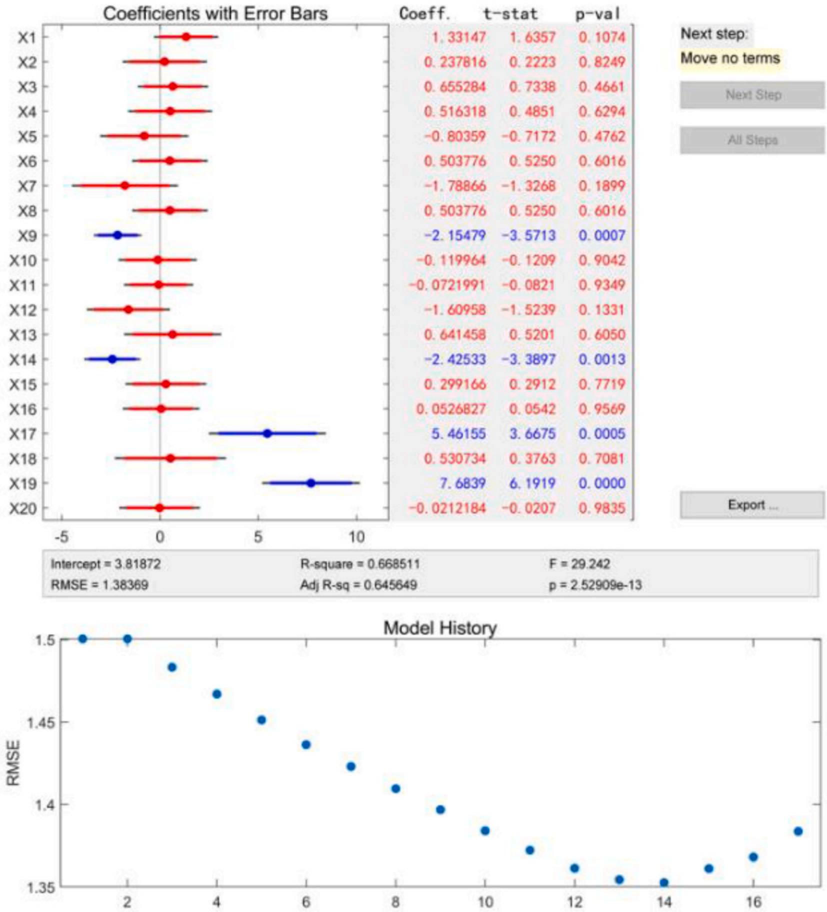

Fig. F2. Stepwise regression result with the dependent variable being affected resilience.

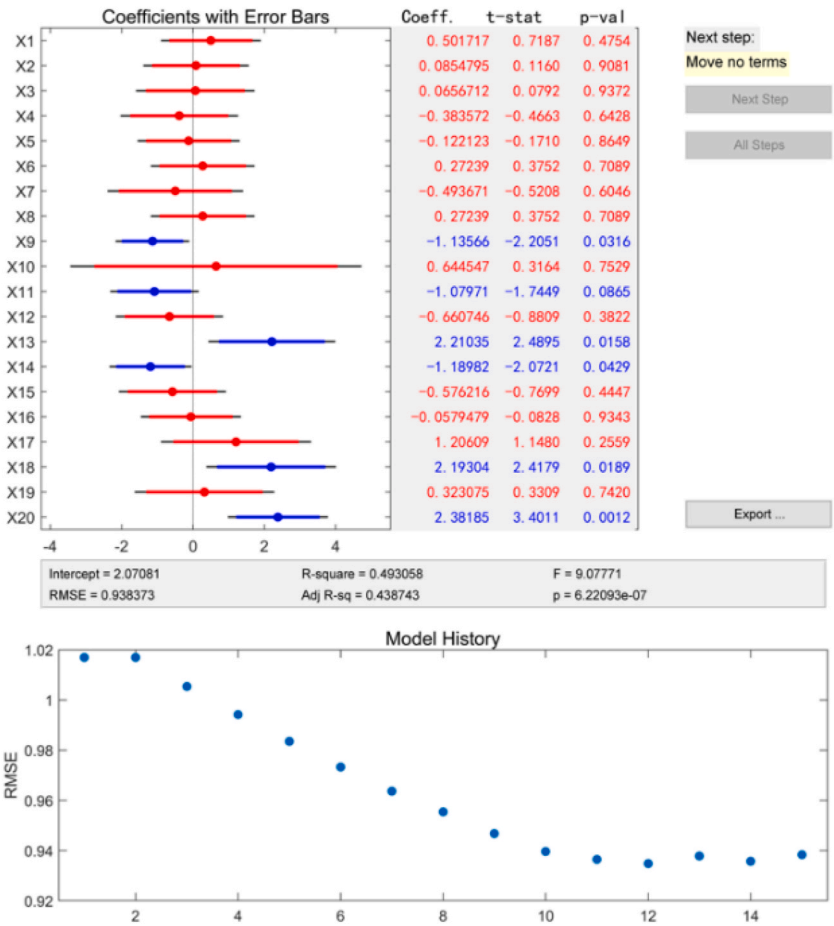

Fig. F3. Stepwise regression result with the dependent variable being economic resilience.

Appendix G. Heatmaps of significant regressors

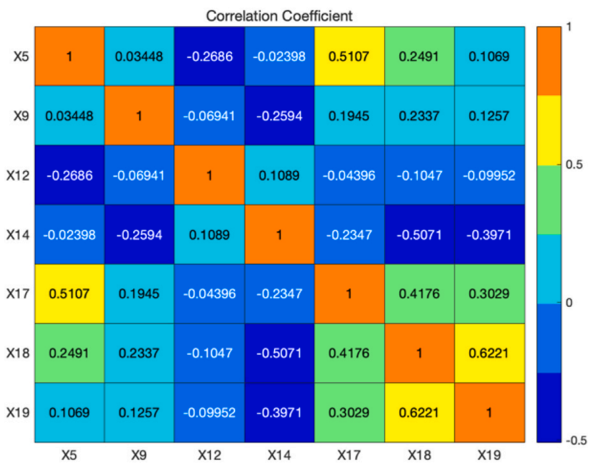

Fig. G1. Heatmap of significant regressors for national resilience.

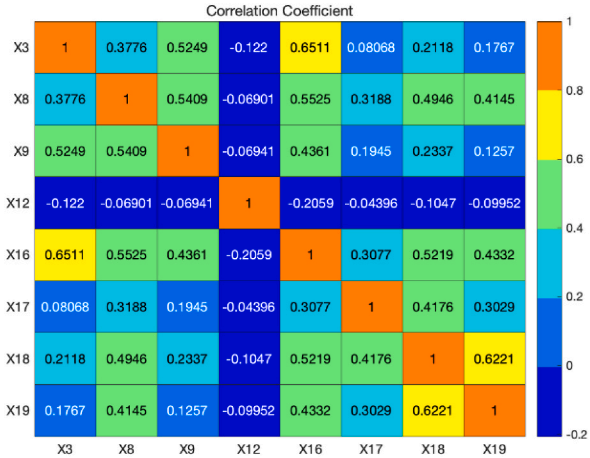

Fig. G2. Heatmap of significant regressors for death resilience.

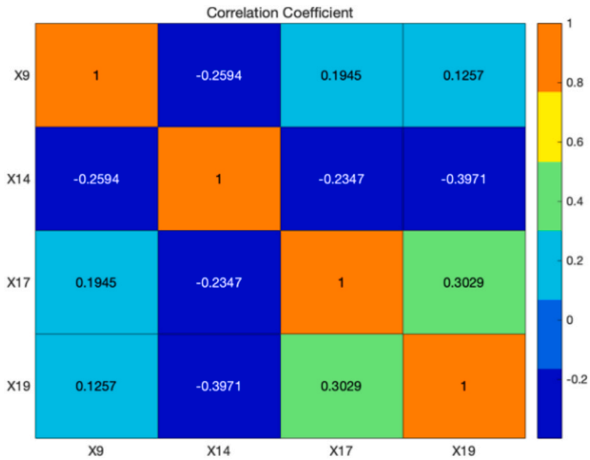

Fig. G3. Heatmap of significant regressors for affected resilience.

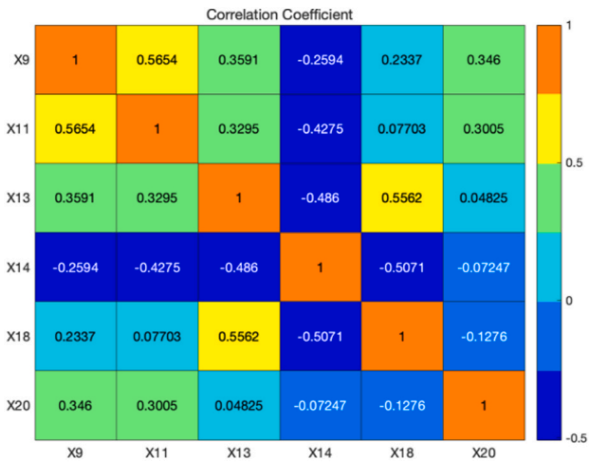

Fig. G4. Heatmap of significant regressors for economic resilience.

Appendix H. Rationality of rank-biased overlap (RBO) approach

Example H1: Suppose that a and b are two ranked lists. Furthermore, $a = [1, 2, 3, 4, 5, 6]$, and $b = [6, 1, 2, 3, 4, 5]$, where '1' denotes the first order and '2' is the second rank, and so forth. Thus, b is only a small turbulence compared with a. However, the Pearson correlation coefficient between a and b is 14.3%, and the Kendall tau rank correlation coefficient between a and b is 33.3%, which both mean a and b are loosely and even not connected to each other. The RBO between a and b is 61.9%, which means that a and b have a relatively high relationship and is in line with our expectation.

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